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Millennial Attitudes Towards Financial Advisors and Emerging Investment Technologies

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Millennial Attitudes Towards Financial Advisors and Emerging Investment Technologies

Abstract

The Millennial cohort has been subject to many generalities regarding their behaviors and preferences when considering investing their wealth. Through use of a factor analysis and k-means cluster segmentation, five distinct clusters of potential investors emerged, each unique in their activity (or lack thereof) towards their portfolios, as well as their desired investment horizon. These clusters further differed in their desire for a traditional financial advisor as opposed to emerging investment algorithms; namely, Cluster 2 prefers the conjunction of an experienced advisor with advanced algorithms as opposed to exclusive use of either option. Further, regarding degrees of control, each Cluster preferred a different degree of control (from Limited to Total) as well as abilities to Adjust or Change an algorithm's parameters. Finally, upon examination of any mediating variables, such as degree of control on portfolio distribution, it was determined that very little statistical significance existed.

Keywords

Finance, Investment, Decision Making, Consumer Choice, FinTech, Algorithms

Disciplines

Business

MILLENNIAL ATTITUDES TOWARDS FINANCIAL ADVISORS AND EMERGING
INVESTMENT TECHNOLOGIES

By

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An Undergraduate Thesis submitted in partial fulfillment of the requirements for the

WHARTON RESEARCH SCHOLARS

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ABSTRACT

The Millennial cohort has been subject to many generalities regarding their behaviors and preferences when considering investing their wealth. Through use of a factor analysis and k-means cluster segmentation, five distinct clusters of potential investors emerged, each unique in their activity (or lack thereof) towards their portfolios, as well as their desired investment horizon. These clusters further differed in their desire for a traditional financial advisor as opposed to emerging investment algorithms; namely, Cluster 2 prefers the conjunction of an experienced advisor with advanced algorithms as opposed to exclusive use of either option. Further, regarding degrees of control, each Cluster preferred a different degree of control (from Limited to Total) as well as abilities to Adjust or Change an algorithm's parameters. Finally, upon examination of any mediating variables, such as degree of control on portfolio distribution, it was determined that very little statistical significance existed.

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INTRODUCTION

Broadly, the goal of this analysis is to prove that homogeneity in approaches to targeting an evolving cohort of future investors is an ineffective strategy for financial advisors and investing algorithms. Many “purchase drivers” exist that influence (a) whether an 18-34-year-old decides to invest a portion of their income (b) what fraction they determine as discretionary funds for their portfolio (c) and what vehicle they choose, whether that be a traditional wealth manager/financial planner or a non-traditional algorithmic-based approach, to invest their assets. These attributes of investigation range from the time-frame of returns, volume requirements, as well as accessibility.

Data was gathered through a 22-question survey, distributed to 121 respondents through Amazon’s Mechanical Turk platform. Respondents were screened to ensure that the sample was representative of the Millennial Cohort in age, as well as from the United States, for simplicity of analysis. This survey included basic multiple-choice questions, likert scales, stack rankings, and a variety of demographic information. To analyze the information, a Principle Components Analysis was employed as well as a K-Means Clustering. Multinomial and Binomial Logistic Regressions, Analyses of Variance, as well as Linear Models were used to determine the potential statistical significance for a mediation analysis.

Ultimately the results encompassed the statistical significance of the relationships between the clusters, the degree of control they desired over an algorithm, and the resulting likelihood to use an investment portfolio bundle (various combinations of exclusively traditional financial advisors, algorithm-based technologies, or some combination of both). Additionally, informative data about the clusters, ranging from their desired time frame of returns, perceived riskiness of asset classes, and attribute importance scores will be beneficial to financial advisors and product designers of algorithms.

LITERATURE REVIEW

Section 1: Millennials and Money

Younger generations, whether they be millennials, GenZ, or beyond, are champions of change when it comes to traditional financial services due to a variety of factors. The Millennial Disruption Index³ reports that 73% of Millennials would be more excited about new offerings in financial services from Google, Amazon, Apple, PayPal, or Square than from their own nationwide bank. Further, roughly 50% of Millennials are counting on tech start-ups (FinTech in particular) to overhaul the way banks work. In “The FinTech Book” there is a large assertion that our generation will outgrow cash at some point⁴, motivated by fin-tech based services “offering trust, transparency, and technology.” However, Millennials aren’t just avoiding holding physical cash - the world is shifting towards seamless transactions, led by this cohort. BBVA research shows that nearly 70% of 18-29 year olds have actively used mobile banking in the past year, whereas less than 35% of members of the 45-59-year-old age bracket have. This startling discrepancy has already affected major financial services organizations, as banks such as Wells Fargo, PNC, and Bank of America have introduced the mobile-payments application Zelle.

Initial research generally covers Millennial investing habits as a whole. In a study conducted at Appalachian State University, Rena Hope Hooker looks to understand the determinants of the target generation’s stock market investment behaviors. Some initial insights are that “an overwhelming majority of millennials do not currently invest in the stock market compared to 51% of Generation X and 48% of Baby Boomers.”⁵ Initial, broad insights revealed that students with negative perceptions of personal investing hold that rewards do not outweigh risks. Most

interestingly, however, is that Hooker's study revealed that 43% of participants in the target demographic would prefer to invest via a trading app on a smart phone, 25% prefer website or online interface, and only 1/3 would prefer in-person brokers. Interestingly, those students with little-to-no business education were found to be more likely to prefer an in-person broker. Conversely, a sizeable portion of low-education investors felt the perceived ease and simplicity of tech-driven investing interfaces would be preferable. A large trend that emerged was the convenience factor – providing access for frequent account checks and quick monetary transactions. Indeed, Hooker found that 54% of respondents reported that they would invest more if it was as easy as shopping online.

⁴Chishti, Susanne, and Janos Barberis. *The FINTECH Book*. John Wiley & Sons, 2016.

⁵Hooker, Rena Hope. *THE DETERMINANTS AND IMPLICATIONS OF MILLENNIALS' STOCK MARKET INVESTMENT HABITS AND OPINIONS*. Master's thesis, Appalachian State University, 2017. Department of Finance, Banking, and Insurance. 5-43.

Section 2: Environmental Effects on Investing Habits

This confirms the belief that millennials are the Amazon and Google generation. Motivated by mistrust in the financial system due to the turmoil of '08-09, this cohort has flocked to robo-advisers that typically use Exchange traded funds (instead of funds that are actively managed), which help keep costs down.⁶ Understanding the context of the typical millennial upbringing is important in this regard: "They were welcomed into the world of investing very differently from those whose first experience was the bull markets of the 1980s and 1990s. As they entered adulthood, they have experienced two major market corrections (the dot-com and housing bubbles) and a wrath of financial scandals (ranging from Enron to Arthur Anderson to Bernie Madoff to the LIBOR rate rigging)."⁷ This impact has surfaced as a tendency for more conservative investor psychology, with holding double the amount of cash (53%) and half as much stock (28%) as the older generations that preceded them. Additionally, there is a strong correlation between whether students view investing as important for money savings and whether or not their parents or grandparents have invested in the stock market before.

However, the external environment is not just limited to the investors. In fact, the somewhat-myopic view of traditional financial advisors, potentially shaped by a past struggle for survival with clients, has left a large segment of the market untapped. Indeed, Millennials have not been a target of the traditional brokerage-based model simply because they don't possess the

⁶Mooney, Attracta. 2017. "Fintech Lures Millennial Investors Away from Asset Managers." *FT.Com*.

⁷Horan, S. M. (2015). The future of wealth management: Unpicking where the puck is going. *CFA Institute*, 1-4

wealth, despite having high earnings potential. “Though most millennials may not have the kind of assets that attract top financial advisers (we can’t all be Mark Zuckerberg), they certainly might one day. And right now, they don’t really want to work with human advisers... they’d rather work with robo-advisers and other technological solutions” says the Journal of Financial Planning.⁸ Unfortunately for asset managers, this seems to be a misconception. The journal further asserts that Millennials make up 14.7% of those with assets in excess of \$2 million, one in five have saved enough in non-retirement accounts to last at least three to five months, and (arguably most importantly) six out of ten expect to be financially better off than their parents⁹. From a perceptual standpoint, it seems that millennials have the desire and ability to invest and store their wealth efficiently, but the most accessible service (frankly, that cares about them) are opportunities within the financial technology space.

Section 3: The Rise of Robo-Advising

Another driver is the low psychological switching costs – the disaffected, disenfranchised millennial is the most prone to switching providers or reviewing investments after seeing an advertisement or having a conversation with peers. The low time-investment costs provided by FinTech are incredibly appealing in this regard.¹⁰ In a similar vein, the actual costs are much lower for robo-advisers, a major motivation force for Millennials. Deutsche Bank Research¹¹ summarizes the costs per annum of the various investment instruments. Traditional financial

⁸“Robo-Advisers: The Gateway to Millennials.” *Journal of Financial Planning*, September 2015, 12-13. Accessed October 2, 2017. EBSCOHost.

⁹Dorsainvil, Rianka R. "Who Are the Next Generation of Planners and Clients?" *Journal of Financial Planning*. September 2015. Accessed October 02, 2017.

¹⁰Williams, Aime. "Millennial Money is Ripping Up the Financial Rule Book." *Financial Times*, Feb 13, 2016. <https://proxy.library.upenn.edu/login?url=https://proxy.library.upenn.edu:7450/docview/1773077161?accountid=14707>.

¹¹Kaya, Orcun. "Robo-advice – a true innovation in asset management." *Deutsche Bank Research*, August 10, 2017, 1-16. Accessed October 2, 2017.

advisors have roughly a 1.2% average fee on investments; however, US based robo-advisors only charge an average of .3% on 100k investments. Additionally, unlike many traditional financial advisors, there are usually no minimum volume requirements for opening a robo-advisor account. This broadens the discussion to that of financial literacy and financial inclusion; many underbanked (or self-perceived to be uninformed) individuals look to robo-advisers as they reduce the cost of advice and give more reasons to embrace them. This in part stems from the fact that millennials are a generation that generally doesn't trust others. Indeed, only 19% of millennials agreed with the statement that "most people can be trusted" (relatively speaking, older generations were more than double that percentage)¹².

This is only confirmed by an earlier study in the Journal of Financial Planning which saw trustworthiness as the most important characteristic of a financial planner. They also felt that "fee-only" financial planners were more likely to possess these characteristics of honesty and trustworthiness, over a commission-based planner. This lack of skin in the game from the planner that is present in FinTech-driven investment vehicles is a major point of differentiation. That said, the millennial cohort interestingly values interpersonal communication strategies when searching for a financial planner – even if said planner is a robo-adviser. The journal reports the top two search strategies are "talk to an expert" and "seek out a referral from an expert in the field."¹³ The bottom line here is that this generation has mixed preferences in terms of evaluation and actually "purchasing" a plan.

¹² Winograd, Morley, and Michael Hais. "How Millennials Could Upend Wall Street and Corporate America." *Governance at Brookings*, May 2014, 2-18. Accessed October 2, 2017. JSTOR.

¹³ "Millennials": Strategies for Financial Planning with a New Generation. Johnson, Scott D, PhD; Larson, Stephen J, PhD, CFP. *Journal of Financial Planning*; May 2009; 22, 5; PsycINFO

Section 4: Attitudes and Algorithms

With a new investment environment comes new behaviors to be explained. Research performed by Dietvorst, Simmons, and Massey describe a psychological phenomenon that they have coined “Algorithm Aversion.” In short, while evidence-based algorithms more accurately predict the future than human forecasters, people are more inclined to pick human-based predictions once they learn that the algorithm is imperfect¹⁴ In their study, on average, participants were 15% less likely to choose a statistical model or algorithm-based platform once they saw the results of the model’s forecasts (41%), as opposed to only seeing the results of the human’s forecasts (56%), or even make an uninformed decision (57%).¹⁵ However, when participants could restrictively modify the model’s forecasts, they were more likely to choose the model, thus performing better. Slight degrees of control and autonomy provided platform users a greater level of trust in the algorithm over a short- and long-term time horizon. For more information on the increase in choice and performance, please see **Exhibit A**.

The complex nature of human’s interactions with algorithm-based technology, including many robo-advising applications, have been an interesting area of exploration. For example, in the *Journal of Consumer Research*, not only does the algorithm itself shape the trust that users place in the system, but also the presentation of the algorithm itself! Regarding the aversion issue, the natural quick fix might be to think that presenting the algorithm as a human would give consumers the best of both worlds. However, Kim, Chen, and Zheng explain that recommendation engines with anthropomorphic visualizations undermine autonomy and

¹⁴Dietvorst, Simmons, Massey. “Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them.” *Management Science*. November 4, 2016.

¹⁵Dietvorst, Simmons, Massey. “Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err.” *Journal of Experimental Psychology: General*. September 25, 201

significantly worsen the overall experience for users.¹⁶ Autonomy is a significant predictor of platform/game enjoyment, and introducing human-like features to the algorithm (including face, body, voice, name, etc...) significantly reduced the perceived autonomy, control, and trust levels that the users had in the game and platform.

FINDINGS

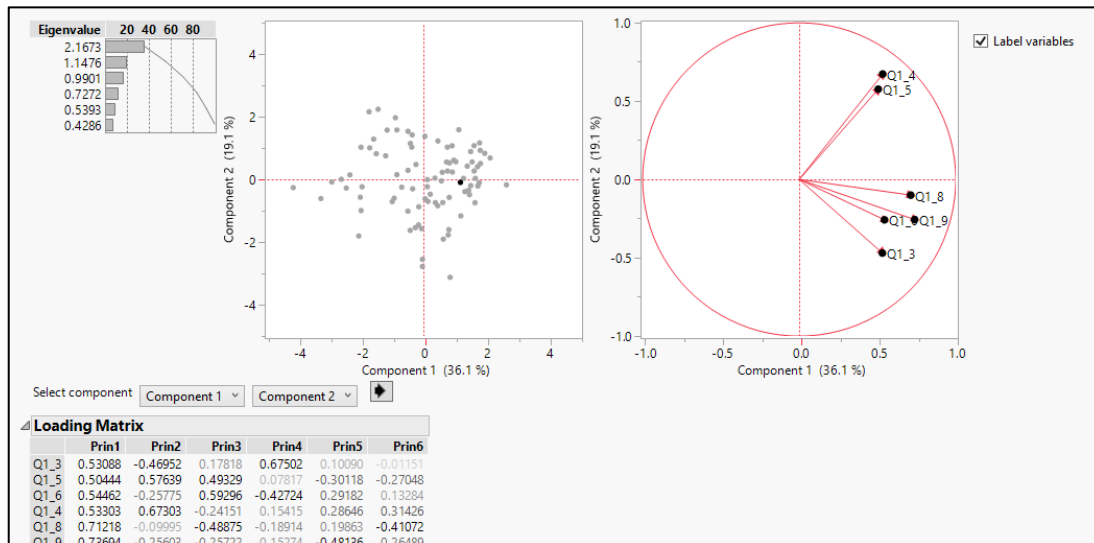
Principle Components Analysis

The first psychographic dimension used to segment the population was “Timeline for Returns,” which spanned from short- to long-term term thinking. The data was elicited through a series of likert scale questions, reproduced below. To moderate for response bias, many questions were reverse coded and confounding data, or responses that provided conflicting information, was removed.

	Strongly Disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree	Not Applicable
I'd prefer investing with a machine/algorithm if it could get equal returns, but in a shorter time frame	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I'd prefer some returns now over more returns later	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When it comes to the stock market, slow and steady definitely wins the race	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I want a financial advisor that can target high returns over time, not just in the next few months	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer a machine/algorithm to manage my money over a person	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My investment future is safer in the hands of a mobile/online app	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

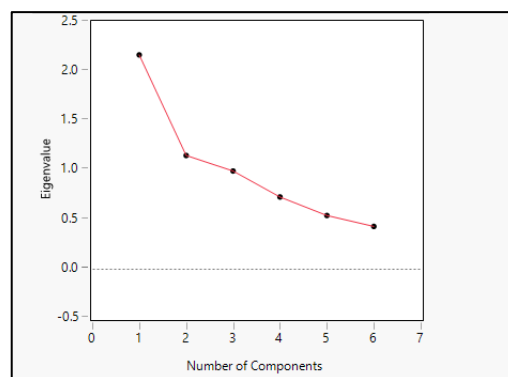
1. Likert Scale Questions - “Timeline for Returns” Psychological Construct

A first run at a Factor Analysis (in XLSTAT) Principle Components Analysis (in statistical software, JMP) with automatic application of factors and a ML (maximum likelihood) estimation method resulted in only one Factor having a significant Eigenvalue, with questions three through six, eight and nine loading onto it. The results of the factor analysis, as well as a summary of the Eigenvalue and Loading Matrix can be viewed below:



2. Summary Statistics and Loading Matrix for First Principle Components Analysis

Upon re-running of the PCA with only those questions included, each loaded significantly (Component 1 Index Scores $\geq .5$) onto the singular factor and contributed positively to an overall factor score of Eigenvalue = 2.1673 (assuming significance at a level ≥ 1) as visualized on the Scree Plot below:



3. Factor 1 – Scree Value of Components

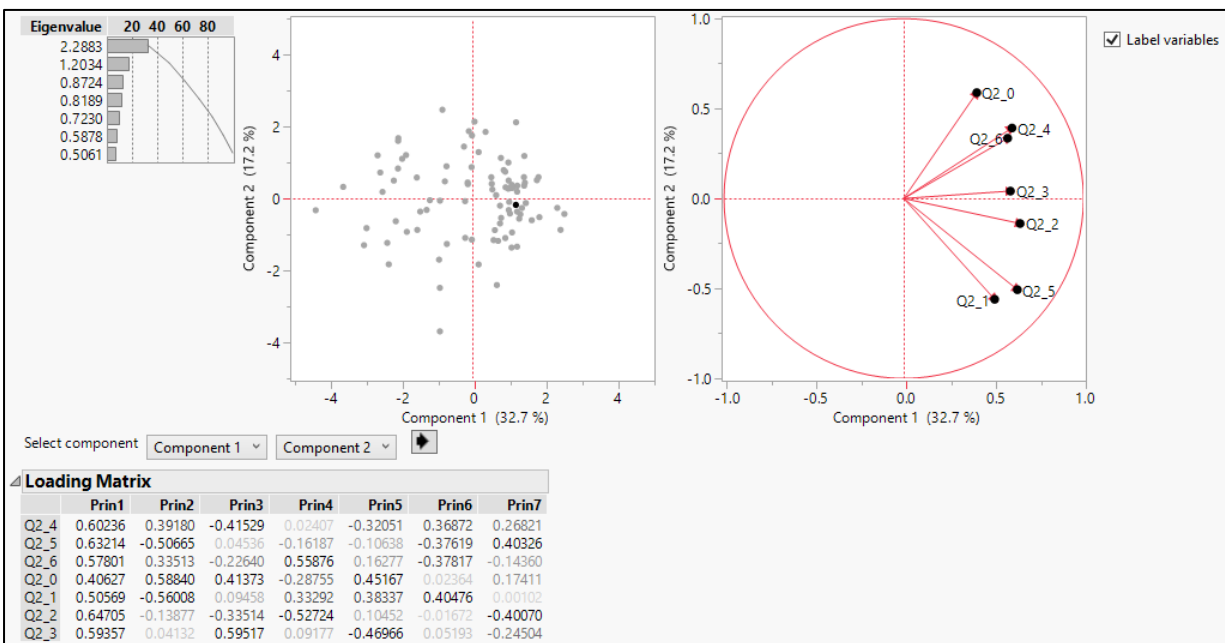
The second factor, “Investor Activity” ranged from Disengaged to Engaged. A “disengaged” investor takes a hands-off approach to their portfolio, often prefers others to manage their investments, and tends to be comfortable going for longer periods of time without checking on

their investments' performance. Conversely, an “engaged” investor is one who actively manages their portfolio or works avidly with a professional or algorithm to receive constant updates on their performance. A sub-set of likert scale questions used to test this dimension is reproduced below:

I prefer someone or something else to manage my investments	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My approach towards investments is incredibly active	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I don't want to check on my investments frequently	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am comfortable with an automated program making investment decisions for me	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

4. Subset of Likert Scale Questions - “Investor Activity” Psychological Construct

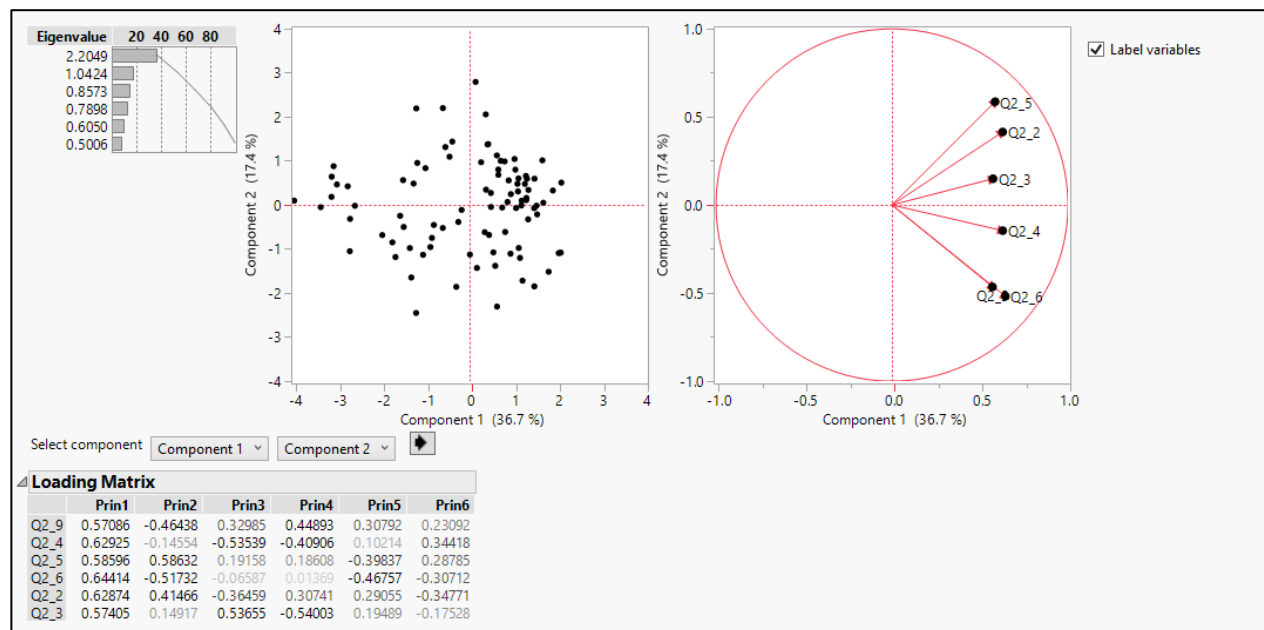
Another Principle Components Analysis was used to test the predictive power of the likert scale questions. To begin, 4 elements of missing data was estimated by nearest neighbors and the components were automatically loaded.



5. Principle Components Analysis of Investor Activity, Automatic Components

This resulted in two components emerging as significant, with Eigenvalues of 2.2883 and 1.2034. Questions 1 and 2 also loaded with index scores of $\sim .41$ and $\sim .50$, respectively.

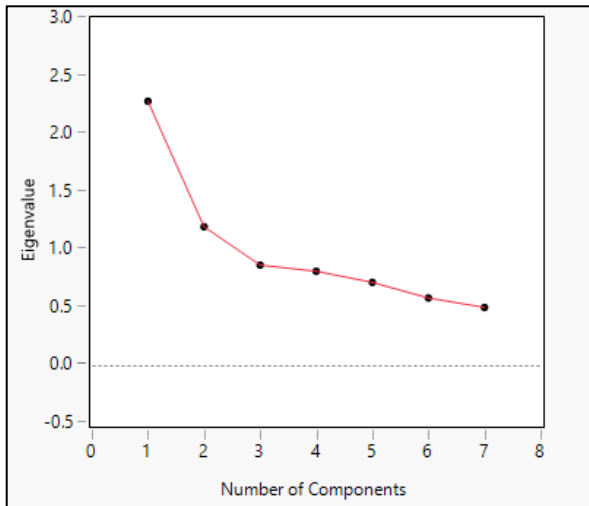
Assuming significance at an Index $\geq .5$, these were removed for a subsequent analysis, where the PCA was forced to adapt to one component. This produced much more promising results, as the select questions all loaded significantly on the first component, with a score plot indicating the first component accounted for 36.7% of the variation in the data set.



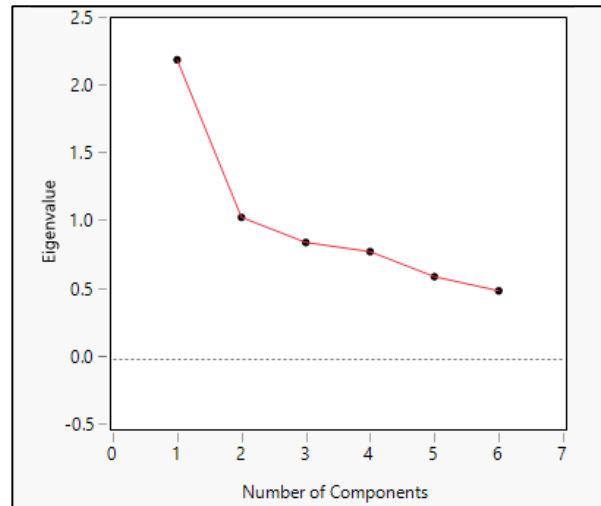
5. Principle Components Analysis of Investor Activity, Controlled Components

The overall Eigenvalue Pareto Plot showed promise with the question set being reduced to Questions two through six and nine. A side-by-side comparison of the two scree plots shows the difference in the significance of Component 1 with removal of “noisy” questions:

2-A



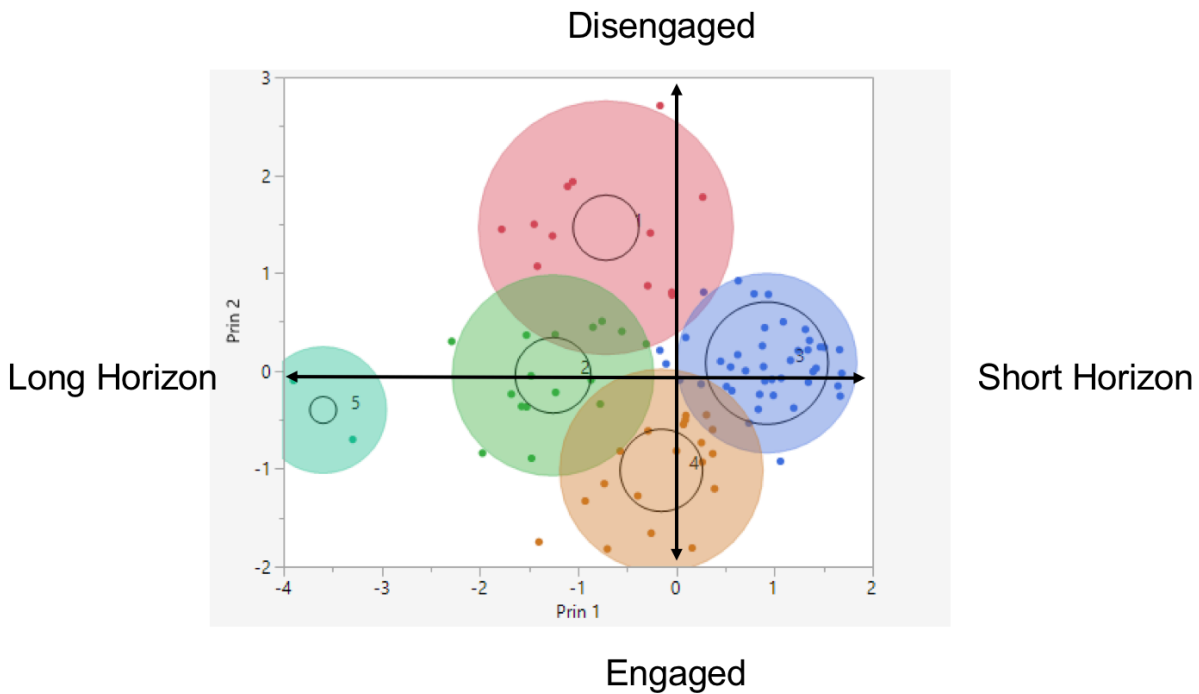
2-B



6. Comparison of Scree Plots to Measure PCA #2 Eigenvalues

K-Means Cluster Analysis

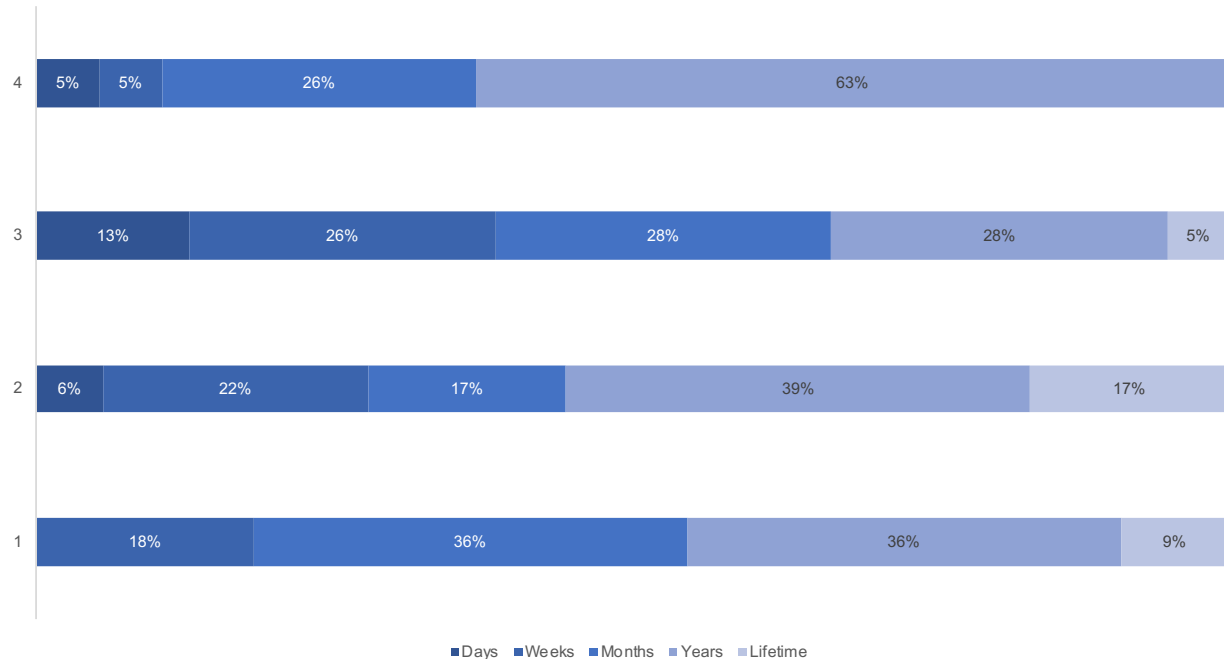
With the two principle components saved down, each respondent was assigned a factor score that was generated from their individual responses to the questions that significantly loaded onto each component. These two factors were then used to generate a k-means cluster analysis with steps from three to six. Ultimately, the most promising cluster was a series of five clusters with relatively evenly distributed size per cluster. For sake of simplicity, the second and fifth cluster (which only contained two responses) were combined. A biplot representation of the cluster analysis output can be viewed below. To add clarity, the two factors were overlaid as axes to visualize the psychographic characteristics of each cluster.



7. Biplot of PCA-Driven K-Means Clustering

Cluster 1 can be characterized by “disengaged” individuals who generally prefer to evaluate investments on a long-term time horizon. Cluster 2 (and 5) represent a cohort of individuals who make long-term investment decisions and are neither strongly engaged or disengaged. Cluster 3 tends to evaluate decisions on a more short-term basis than the average population as well as tends to be slightly more disengaged, while not particularly significant. Finally, Cluster 4 is highly engaged and is active in terms of their approach to managing their portfolios; however, they are fairly split in terms of what timeframe they are evaluating investments.

The time frame in which clusters are evaluating investment decisions was further confirmed through a subsequent question, the results are summarized in the chart below:

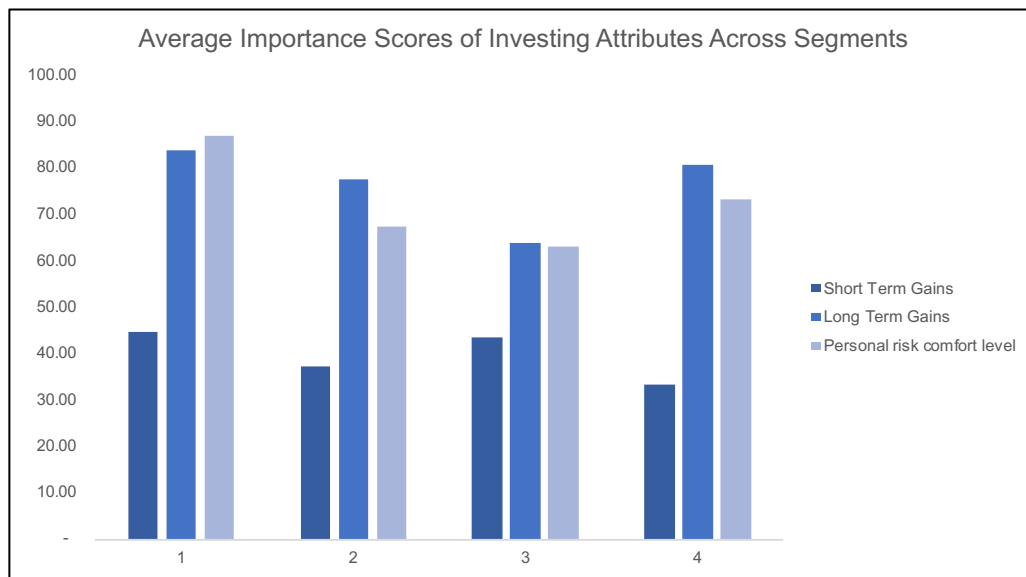
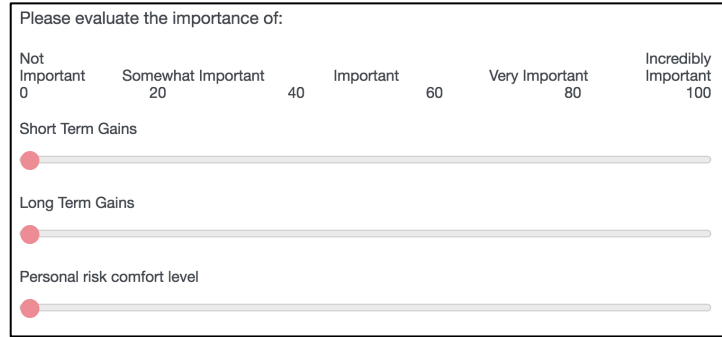


8. Investment Horizon Preference by Segment

Unsurprisingly, Cluster 2 is the cohort that has the largest percentage (17%) of those who evaluate investments on a “lifetime” basis, whereas Cluster 3 has the greatest percentage of short-term preferences (13% for Days, 26% for Weeks, and 28% for only Months). Interestingly, Cluster 4 has the largest portion of individuals who prefer to look at returns on a yearly basis (63%), a somewhat “neutral” option considering the difference between investing month-to-month and investing with the hope of reaping returns after the course of a lifetime.

Cluster Profiles and Insights

The next step was to identify whether a Cluster saw personal risk tolerance and asset volatility as a more immediate factor on whether or not to invest. This was elicited through a simple importance assignment exercise, illustrated below:

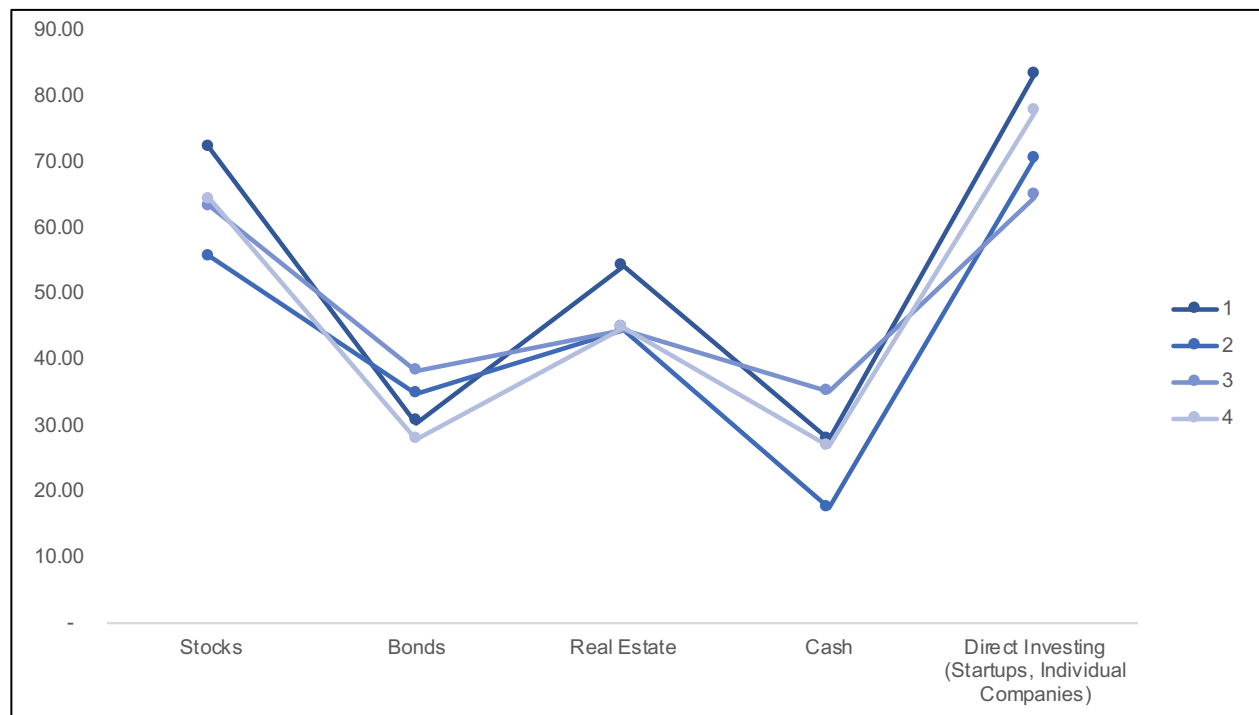


9. Survey Distribution – Importance Testing of Time vs Risk

While all clusters demonstrated characteristics in line with their psychographic personalities generated from the k-means clustering, it's important to note that Cluster 1 sees risk comfort level as a more definitive attribute in whether or not they would invest, as well as how much they would invest and what they would invest in, then the time horizon. An additional insight is that even the Clusters that were more short-term focused in nature felt that long-term gains were always a more important purchase driver.

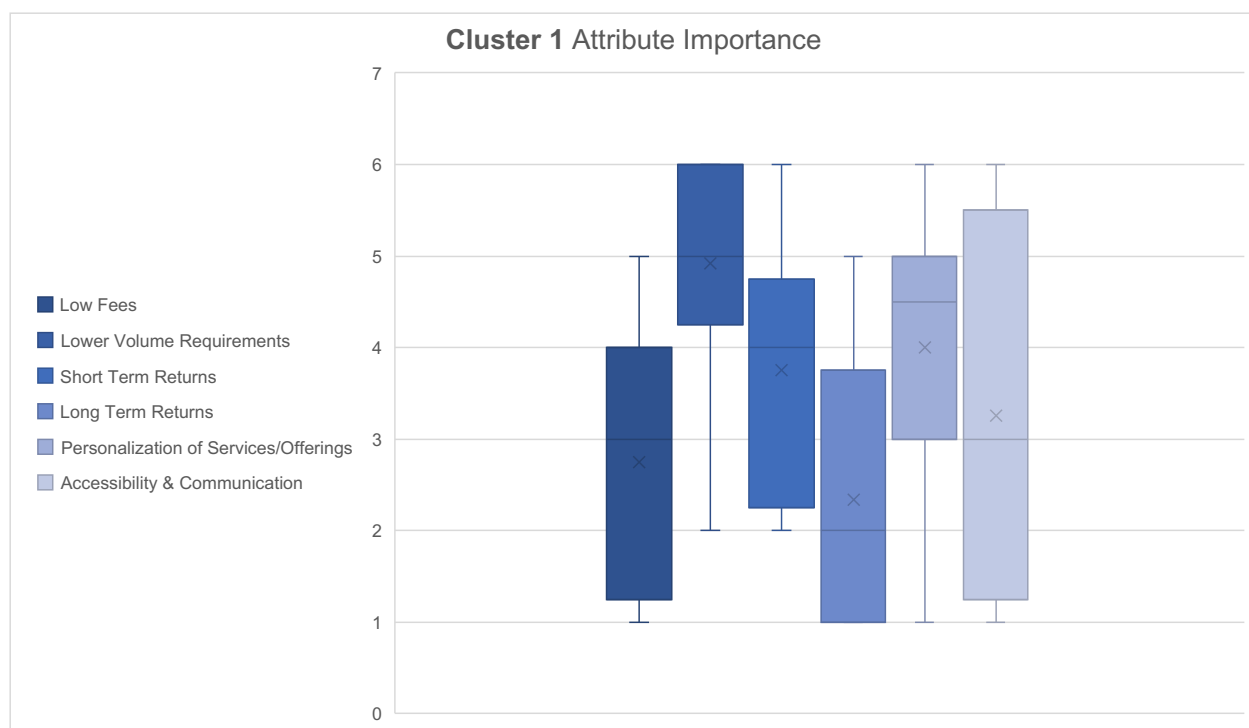
Each cluster had different perceptions on the riskiness of various asset classes as well. On average, Cluster 3 felt investing was less risky, whereas Cluster 1 seemed to be the most

sensitive and assigned the highest risk scores across the board, except for bonds, which they viewed as a safer asset than the other cohorts. More detail is provided below:

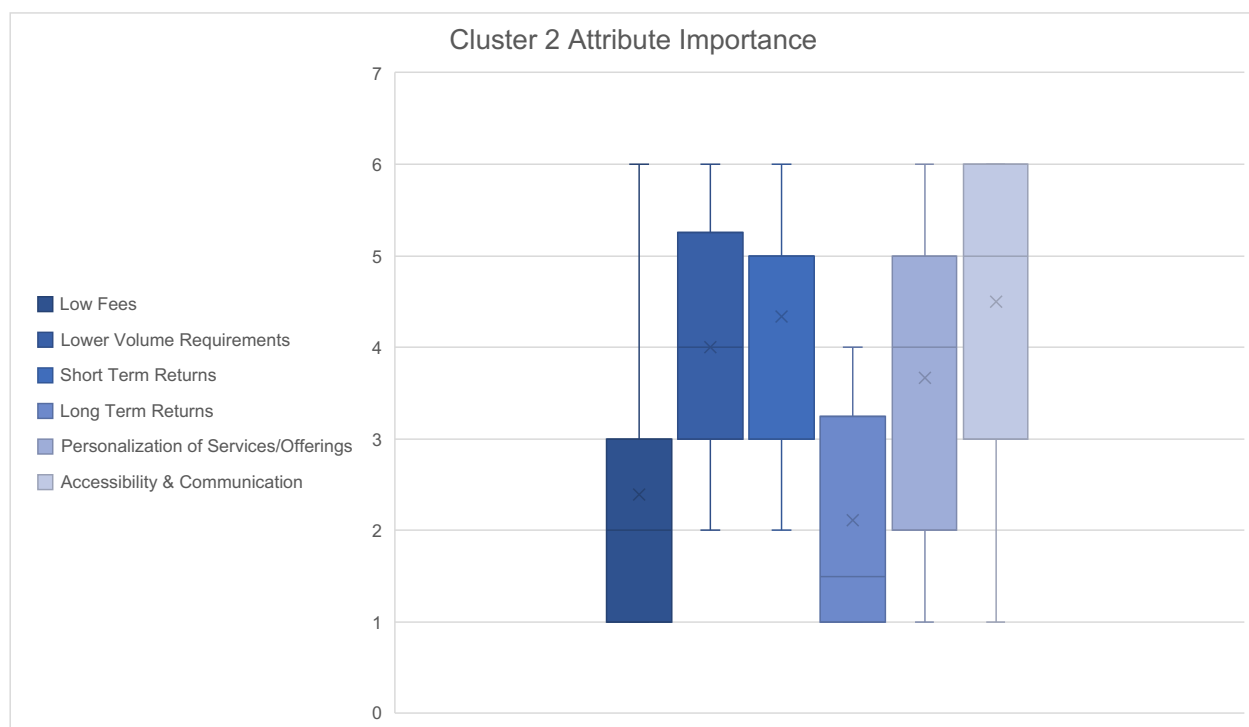


10. Risk Levels Associated with Investment Instruments (Scaled 0-100), by Cluster

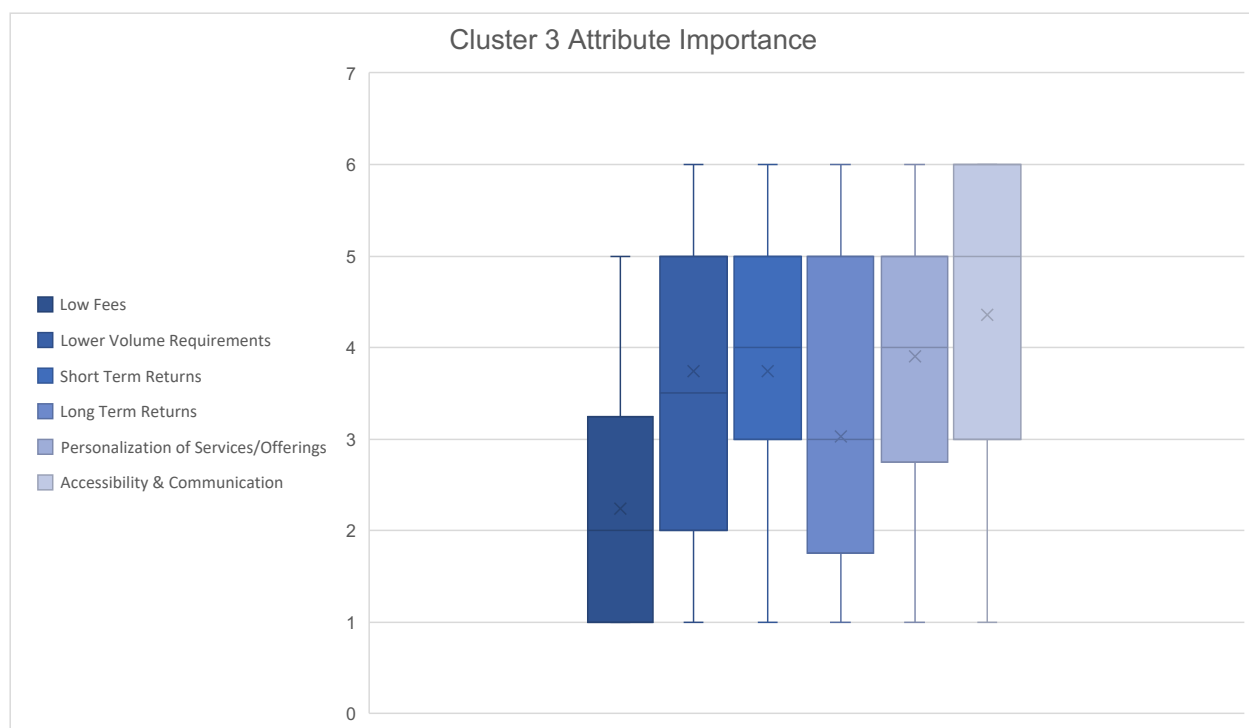
The research then turned to evaluating the Clusters' various preferences towards attributes that would guide a purchase decision when choosing a specific type of financial advisor. Driven by rank-order questions, respondents would place value on certain attributes. The means and summary statistics are visualized in the box charts below:



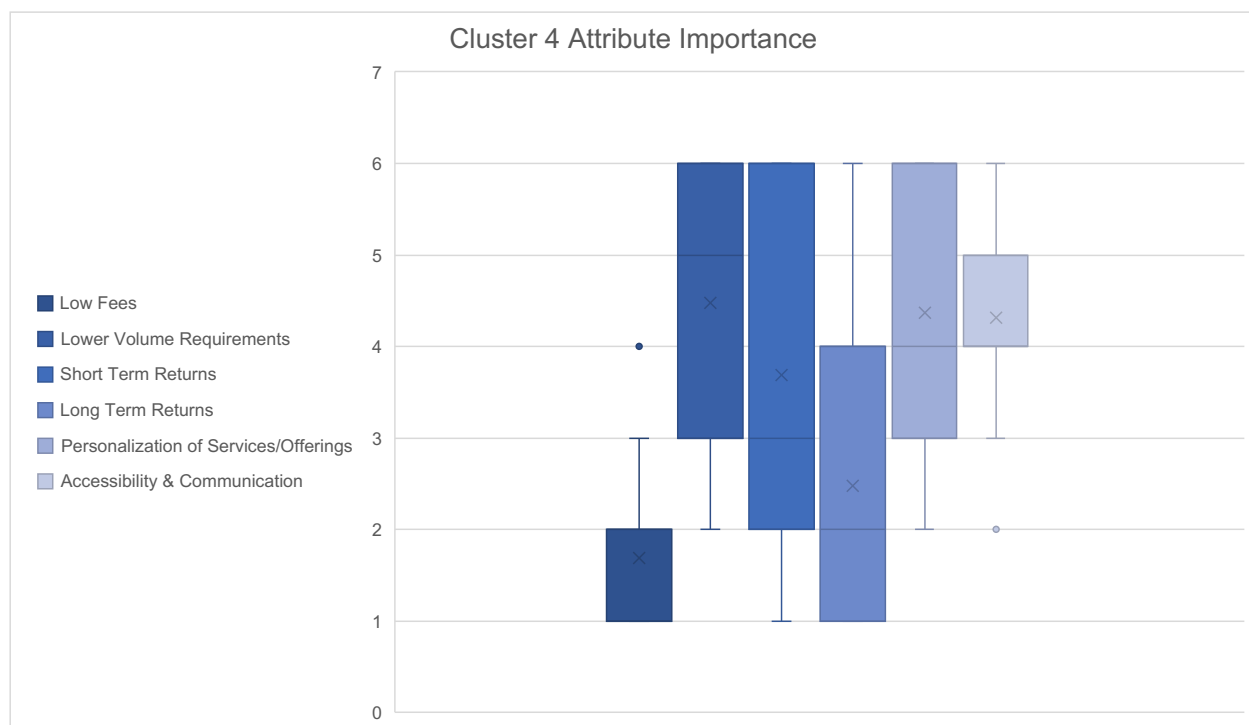
11-A: Cluster 1 Preferences



11-B: Cluster 2 Preferences



11-C: Cluster 3 Preferences



11-D: Cluster 4 Preferences

Across the board, the Clusters are looking for low fees to drive their investment choices. This is a recurring theme in the existing research behind wealth management and financial planning discussions – a race to the bottom in terms of fee cutting has reduced margins for financial planners and has made client relationships much more taxing. This has also given rise to a superficial belief that algorithms will full disrupt the industry, putting human advisors out of business, as they are most suited to cut fees to a nominal level.

However, Cluster 2 shows nearly indifferentiable rankings with every other attribute, indicating an even playing field for traditional and algorithmic advisors alike. Short-term returns do not seem alluring to prospective investors in the field, save for Clusters 3 and 4, which are naturally more short-term focused in nature.

Demographically, Clusters were analyzed on dimensions of (1) age, (2) gender, (3) education level, (4) investable assets, and (5) self-evaluated “financial literacy” levels. For age, Clusters 2 and 4 were younger than the average sample who participated in the survey. Regarding Gender, Clusters 1, 2, and 4 were predominately male (with Cluster 4 being a disproportionately large, 74% male).

AVERAGE AGE		GENDER		
1	28.67	1	12.00	
2	28.11	Female	4	33%
3	28.39	Male	8	67%
4	27.37	2	18.00	
Overall Average	28.16	Female	6	33%
		Male	12	67%
		3	42.00	
		Female	24	57%
		Male	18	43%
		4	19.00	
		Female	5	26%
		Male	14	74%

12. Cluster-Level Average Respondent Age and Gender

The most educated Clusters include Cluster 2, with 22% of the sample having a master's or Doctorate degree, as well Cluster 1. This trend continues with the evaluation of Financial Literacy:

EDUCATION		
1	12.00	
BA/BS/Other Undergraduate Degree	5	42%
High School	1	8%
Masters or Doctorate	2	17%
Some College	4	33%
2	18.00	
BA/BS/Other Undergraduate Degree	8	44%
Masters or Doctorate	4	22%
Some College	6	33%
3	42.00	
BA/BS/Other Undergraduate Degree	20	48%
Masters or Doctorate	4	10%
Some College	15	36%
Some High School	3	7%
4	19.00	
BA/BS/Other Undergraduate Degree	8	42%
High School	2	11%
Masters or Doctorate	2	11%
Some College	7	37%

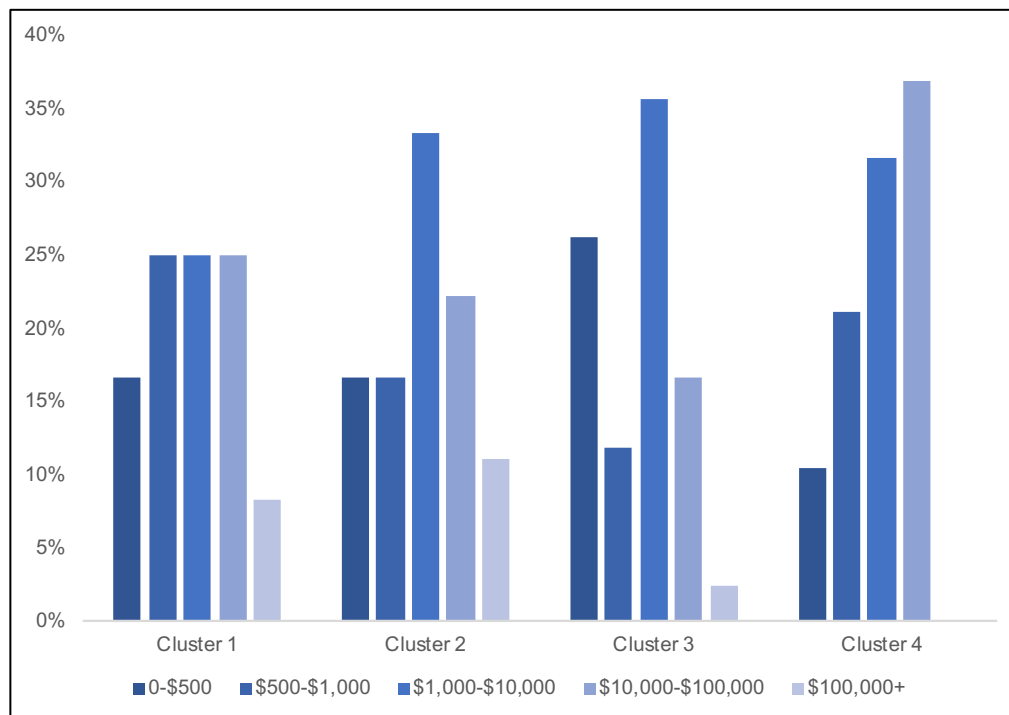
FINANCIAL LITERACY		
1	12.00	
Below Average	6	50%
Above Average	4	33%
High Level of Financial Proficiency	2	17%
2	18.00	
Little to No Financial Literacy	1	6%
Below Average	7	39%
Above Average	7	39%
High Level of Financial Proficiency	3	17%
3	42.00	
Little to No Financial Literacy	7	17%
Below Average	17	40%
Above Average	13	31%
High Level of Financial Proficiency	4	10%
Prefer not to answer	1	2%
4	19.00	
Below Average	7	37%
Above Average	12	63%

13. Cluster-Level Average Education and Financial Literacy

Cluster 2 has 39% of the sample with perceived above-average financial literacy and 17% of respondents believing they have a “high level of financial proficiency.” An interesting takeaway presents itself as the relationship between an increasing level of educational background and financial experience in coordination with a greater appreciation and focus on a longer-term time

horizon for investment returns. This aligns well with existing thinking discussed in the literature review.

The next piece of information is the investable assets available to each cluster.

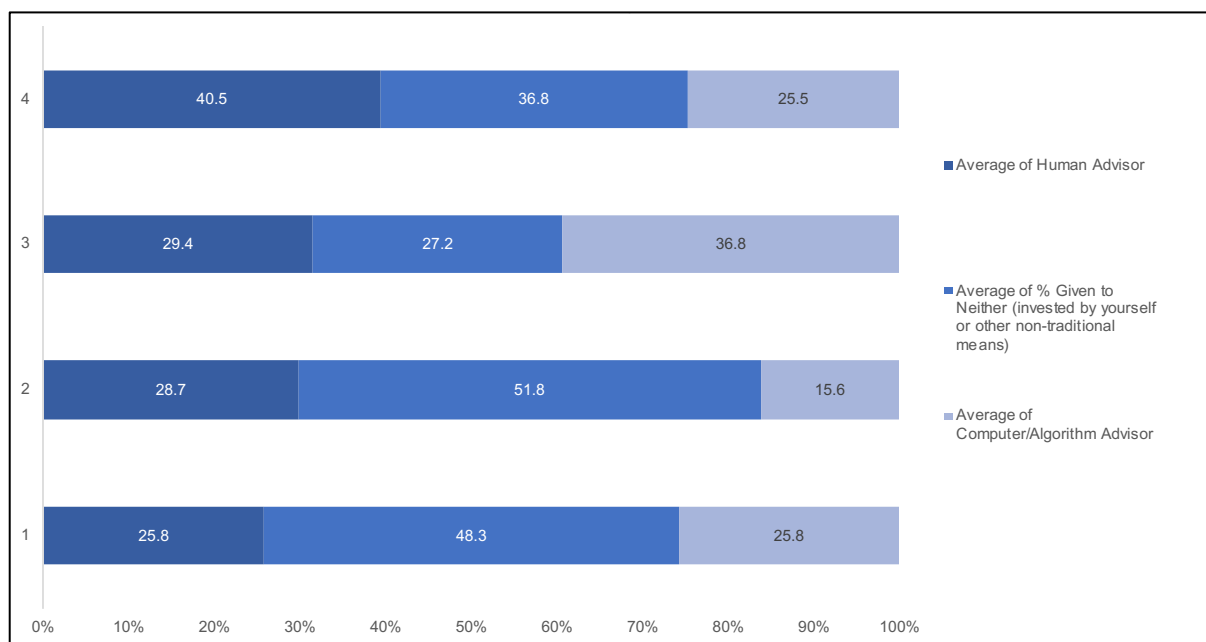


14. Cluster-Level Percentage of Investable Assets

While Cluster 1 has a fairly uniform distribution at around 25% for the mid-three tiers (\$500 through \$100,000), the truly interesting case is Cluster 2, which has a normal distribution, including the largest percentage (11%) of respondents who have investable assets upwards of \$100,000. This clearly makes Cluster 2 an attractive target for wealth managers and financial advisors alike. Additionally, Cluster 4 scales linearly upwards, capping off with roughly 37% of respondents indicating that they have \$10,000 to \$100,000 investable assets.

Portfolios Allocations and Algorithm Preferences

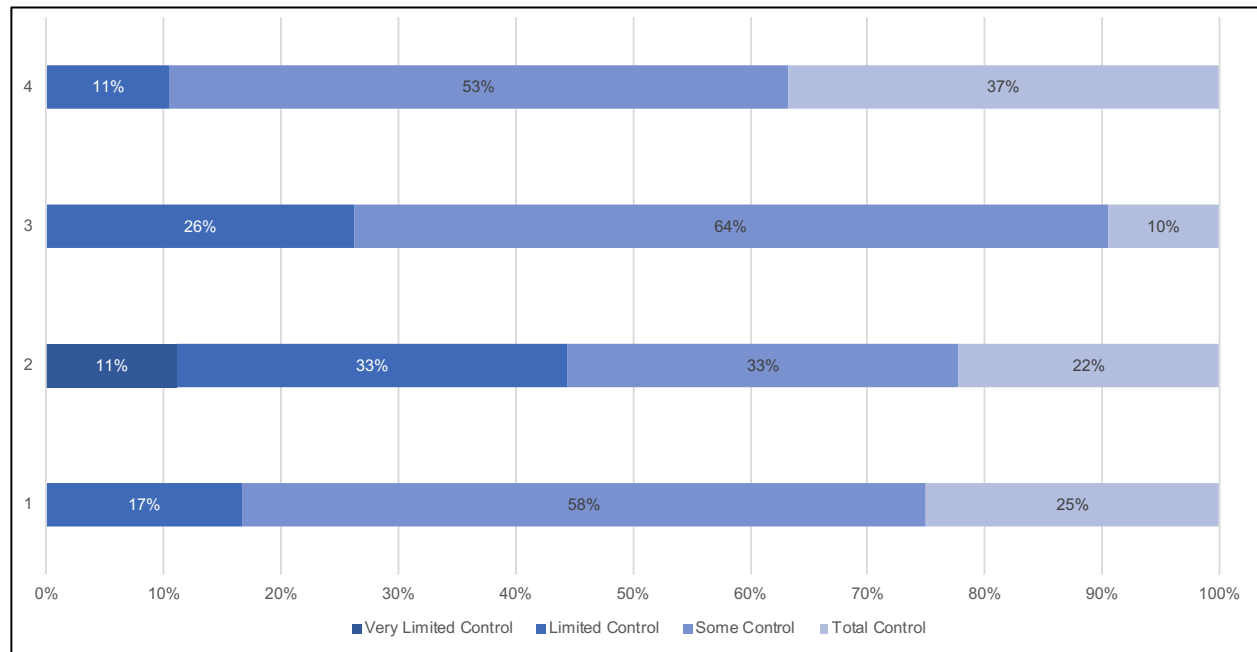
As a baseline, each Cluster initially provided the details on what their ideal allocation of assets would be, either to a Human Advisor, Algorithmic Advisor, or Neither, summing the choices to 100%.



15. Average Percentage of Investable Assets Allocated to Investment Options

The results indicated that Cluster 2 was the most self-sufficient, prioritizing investing the assets by themselves or through other means (51.8%) over a Human Advisor (28.7%) and an Algorithm (15.6%). Generally more educated and looking for longer-term returns, Cluster 2 sensibly would like to own the most amount of control over their portfolio, but their psychographic split between being engaged and disengaged potentially justifies why an almost equal amount of their portfolio would be allocated to third-parties for advising purposes. Cluster 3 had the most preference for Algorithms (36.8%) and Cluster 4 had the most preference for Human Advisors (40.5%).

However, despite a range of investment into algorithms anywhere from 15.6% to 36.8% of assets, the various Clusters had drastically different preferences in terms of the level of control they exerted over various investment algorithms.



16. Control over Parameters in an Investment Algorithm, by Cluster

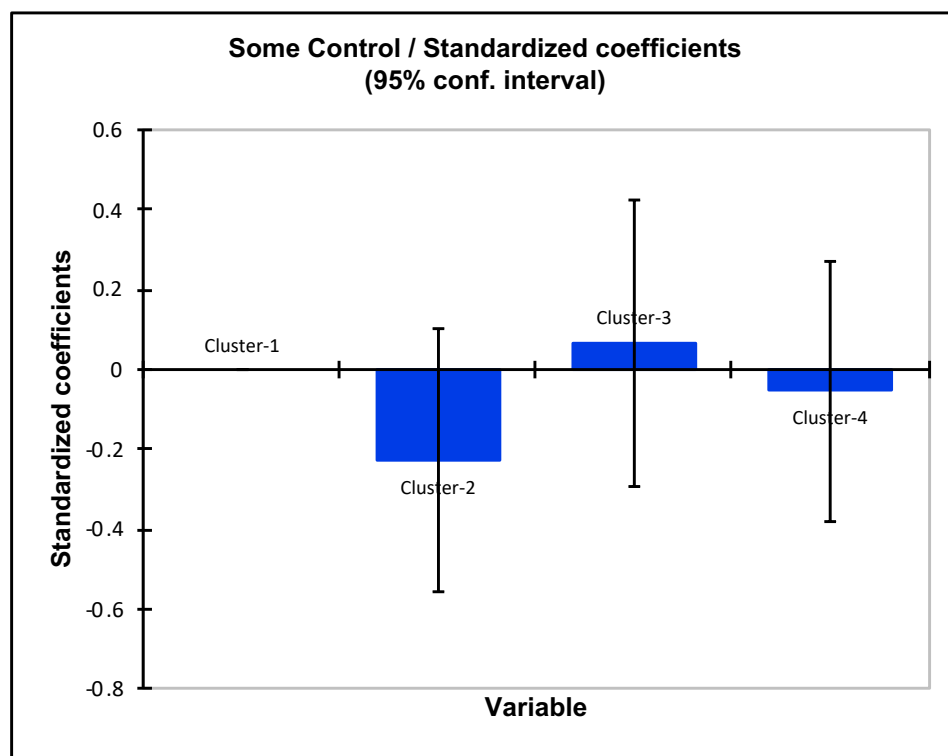
When explaining this to individuals, the degrees of control were framed as follows:

Very Limited Control	<i>“Almost all decisions are made automatically, without my approval”</i>
Limited Control	<i>“I can adjust specifications with limited degree, but the algorithm can operate on its own if I choose”</i>
Some Control	<i>“I dictate my investing strategy, and the algorithm executes without need for my attention”</i>
Total Control	<i>“I manage everything, except the particulars of the actual trades themselves”</i>

Clusters 1 and 3 stand out as the groups that value “Some Control” over their algorithms, with 58% and 64% of respondents indicating they would prefer that degree of control, respectively. Additionally, it’s important to note that 37% of Cluster 4 sought to have total control over the algorithm parameters.

A Mediation Analysis

Provided this disparity in the Cluster’s preference over Algorithm control, it made sense to test the statistical significance of relationship between Cluster and likelihood of responding to the degrees of control, using “very limited control” as a control case.



Model parameters (Variable Some Control):

Source	Value	Standard error	Wald Chi-Square	Pr > Chi²	Wald Lower bound (95%)	Wald Upper bound (95%)	Odds ratio	Wald Lower bound (95%)	Wald Upper bound (95%)
Intercept	0.336	0.586	0.330	0.566	-0.811	1.484			
Cluster-1	0.000	0.000							
Cluster-2	-1.030	0.770	1.788	0.181	-2.539	0.479	0.357	0.079	1.615
Cluster-3	0.251	0.668	0.141	0.707	-1.058	1.561	1.286	0.347	4.764
Cluster-4	-0.231	0.744	0.096	0.756	-1.690	1.228	0.794	0.185	3.413

Equation of the model (Variable Some Control):

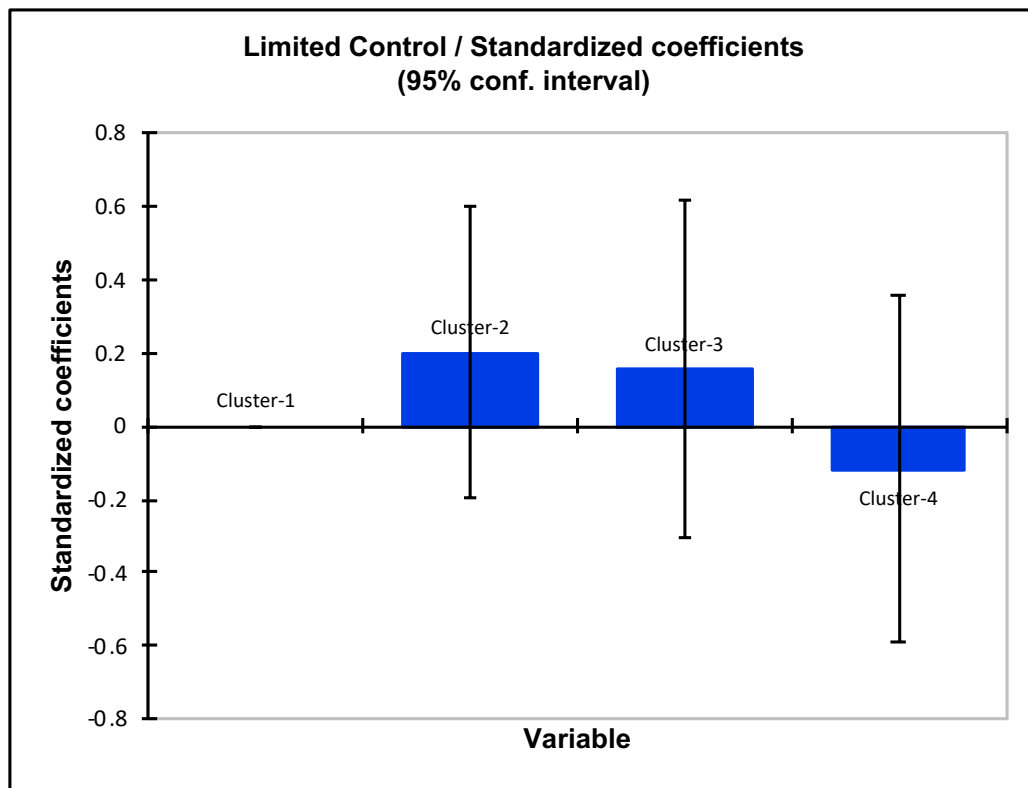
$\text{Pred}(\text{Some Control}) = 1 / (1 + \exp(-(0.336472236621213 - 1.02961941718116 * \text{Cluster-2} + 0.251314428280906 * \text{Cluster-3} - 0.231111720963386 * \text{Cluster-4})))$

17. Binary Logistic Model of “Some Control” over Model Parameters

The model concluded that, with a limited degree of significance, Cluster 2 had a negative predictive relationship with an individual desiring “some control” over an investment algorithm.

In fact, Cluster 3 was the only one with a statistically significant positive likelihood that they would prefer that degree of control, to an extent.

The next consideration was examining the relationship at a lower level – limited control.



Model parameters (Variable Limited Control):

Source	Value	Standard error	Wald Chi-Square	Pr > Chi ²	Lower bound	Upper bound	Odds ratio	Lower bound	Upper bound (95%)
Intercept	-1.609	0.775	4.317	0.038	-3.128	-0.091			
Cluster-1	0.000	0.000							
Cluster-2	0.916	0.922	0.988	0.320	-0.891	2.723	2.500	0.410	15.230
Cluster-3	0.573	0.850	0.455	0.500	-1.093	2.240	1.774	0.335	9.394
Cluster-4	-0.531	1.076	0.243	0.622	-2.641	1.579	0.588	0.071	4.851

Equation of the model (Variable Limited Control):

Pred(Limited Control) = $1 / (1 + \exp(-(-1.6094379124341 + 0.916290731874151 * \text{Cluster-2} + 0.573345980747321 * \text{Cluster-3} - 0.530628245395595 * \text{Cluster-4})))$

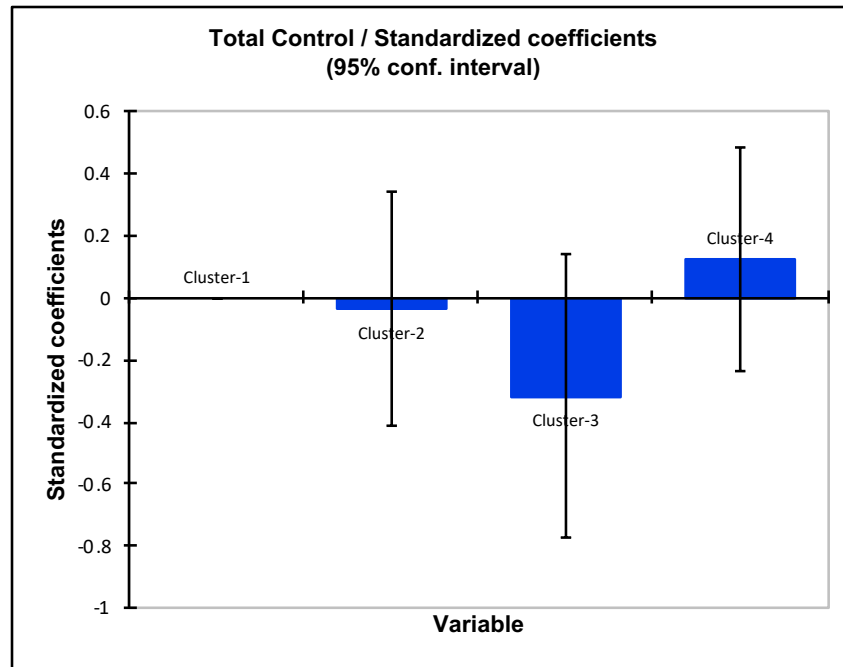
Standardized coefficients (Variable Limited Control):

Source	Value	Standard error	Wald Chi-Square	Pr > Chi ²	Lower bound	Upper bound (95%)
Cluster-1	0.000	0.000				
Cluster-2	0.201	0.202	0.988	0.320	-0.196	0.598
Cluster-3	0.158	0.234	0.455	0.500	-0.301	0.616
Cluster-4	-0.119	0.241	0.243	0.622	-0.592	0.354

18. Binary Logistic Model of “Limited Control” over Model Parameters

In this case, Cluster 2 had the most positive relationship that was statistically significant, indicating that above the other Clusters, it was most likely that a member of this cohort would prefer a relationship with their algorithm in which they set the model parameters and let the algorithm run, self-correct, and perform ultimately without much oversight or intervention.

The final level to examine was “Total Control”



Model parameters (Variable Total Control):

Source	Value	Standard error	Wald Chi-Square	Pr > Chi²	lower bound	upper bound	Odds ratio	Lower bound	Upper bound (95%)
Intercept	-1.099	0.667	2.716	0.099	-2.405	0.208			
Cluster-1	0.000	0.000							
Cluster-2	-0.154	0.875	0.031	0.860	-1.869	1.561	0.857	0.154	4.764
Cluster-3	-1.153	0.849	1.843	0.175	-2.817	0.511	0.316	0.060	1.667
Cluster-4	0.560	0.819	0.467	0.494	-1.045	2.165	1.750	0.352	8.712

Equation of the model (Variable Total Control):

$$\text{Pred(Total Control)} = 1 / (1 + \exp(-(-1.09861228866811 - 0.154150679827258 * \text{Cluster-2} - 1.1526795080574 * \text{Cluster-3} + 0.559615787935838 * \text{Cluster-4})))$$

Standardized coefficients (Variable Total Control):

Source	Value	Standard error	Wald Chi-Square	Pr > Chi²	lower bound	upper bound (95%)
Cluster-1	0.000	0.000				
Cluster-2	-0.034	0.192	0.031	0.860	-0.411	0.343
Cluster-3	-0.317	0.233	1.843	0.175	-0.774	0.141
Cluster-4	0.125	0.184	0.467	0.494	-0.234	0.485

19. Binary Logistic Model of “Total Control” over Model Parameters

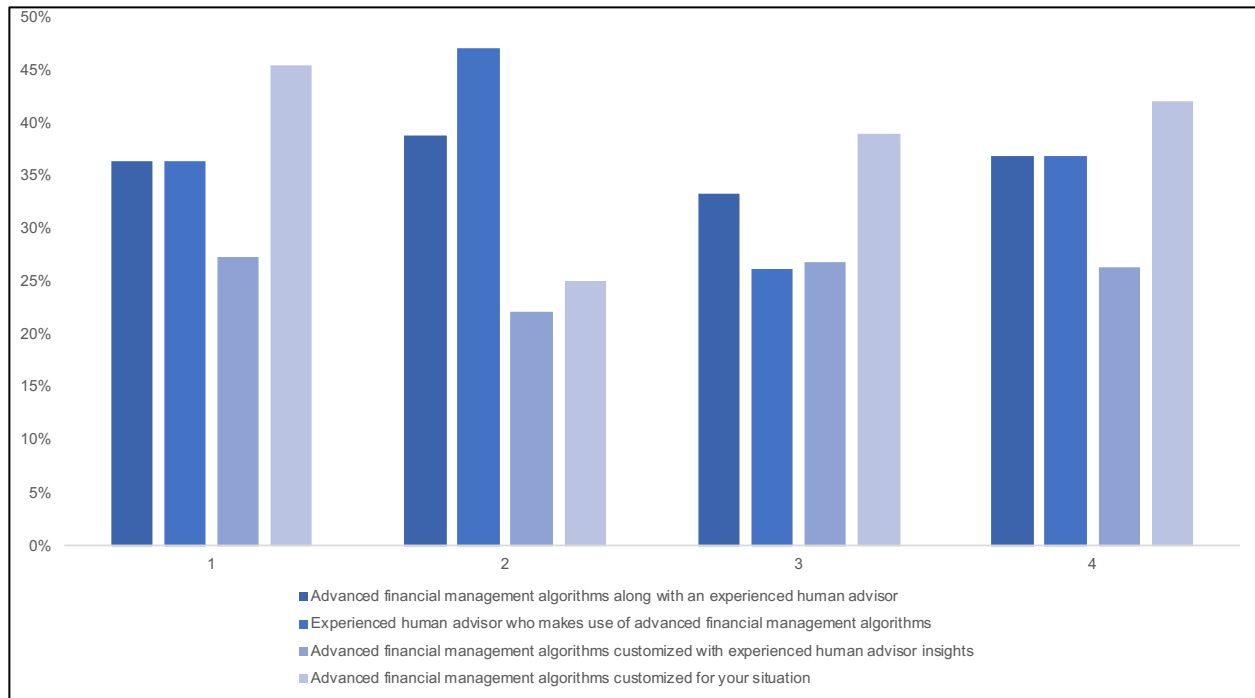
Cluster 4 was the only group that had a positive relationship with predicting that it would desire “Total Control.” Interestingly, Clusters 2 and 3 had negative relationships, most notably being Cluster 3. A key takeaway from this would be defining the type of user interface or enrollment

platform for a target segment – for example, if the desire was to engage with Cluster 4, more flexible options could incentivize them to pay higher fees or commit more capital.

Having tested the relationships between the different Clusters and their desired degrees of control. The next step in the mediation analysis was to test the relationship between the clusters and the percentage of their investable assets (a dependent variable) they would be willing to various bundles. These included four different options:

- (1) Advanced financial management algorithms along with an experienced human advisor
- (2) Experienced human advisor who makes use of advanced financial management algorithms
- (3) Advanced financial management algorithms customized with experienced human advisor insights
- (4) Advanced financial management algorithms customized for your situation

A high-level summary of each Cluster’s “extremely likely” use case for these options is detailed below. At first blush, the research showed a broad range of preferences, generally with Clusters 1, 3, and 4 gravitating towards Algorithms customized for your situation. However, Cluster 2 differed in that the group preferred Experienced human advisor who makes use of advanced financial management algorithms. Interestingly, by virtue of choice architecture, this was the only option that lead with a human-based approach, indicating a potential for Cluster 2 to be a valuable sub-segment for traditional Financial Advisors.



20. "Extremely Likely" Use of Investment Options, by Cluster

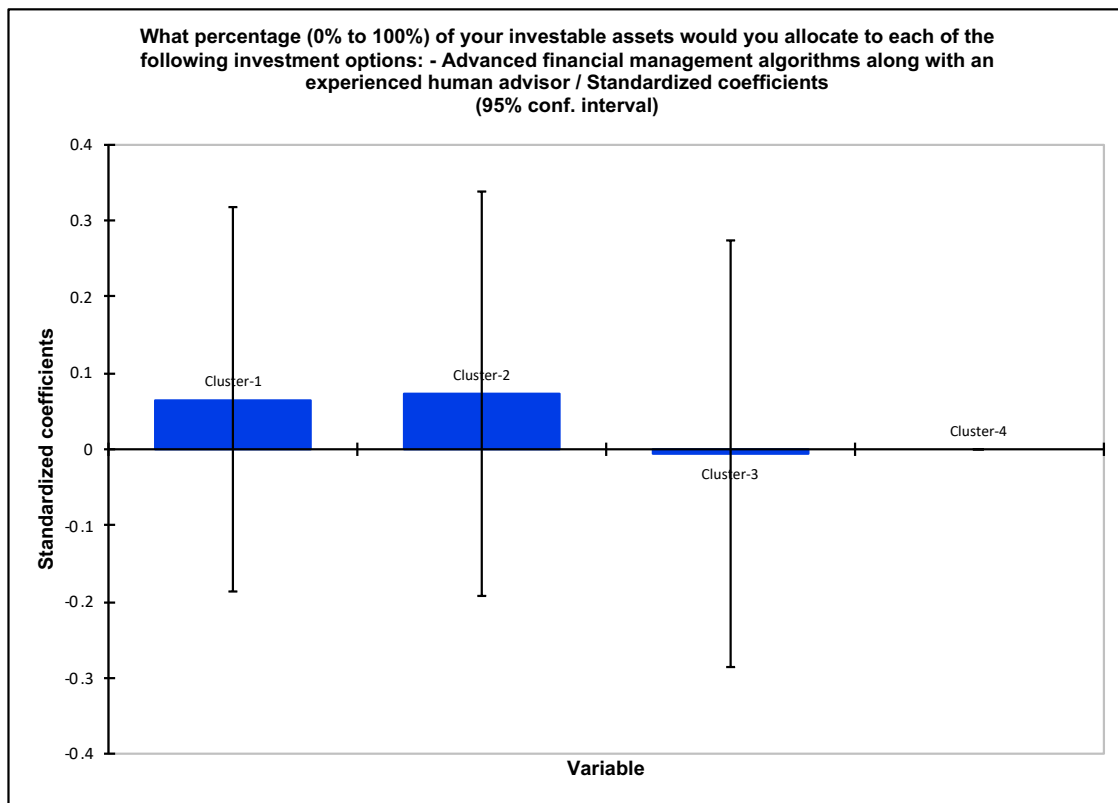
To test the statistical significance of the relationship further, multinomial logistic regressions were conducted holding "neither likely or unlikely" as the control variable. An ANOVA analysis provided a correlation matrix (reproduced below) that indicated a broad spectrum of relatively weak relationships between the various clusters and the likelihood of using a potential option. These ranged from $[-.110, .650]$. It's also important to note that Clusters 2 and 3 as well as 4 and 3 are most dissimilar.

Correlation matrix:

	Cluster-1	Cluster-2	Cluster-3	Cluster-4	Advanced financial management algorithms along with an experienced human advisor	Experienced human advisor who makes use of advanced financial management algorithms	Advanced financial management algorithms customized with experienced human advisor insights	Advanced financial management algorithms customized for your situation
Cluster-1	1	-0.194	-0.361	-0.200	0.053	0.003	0.004	-0.057
Cluster-2	-0.194	1	-0.460	-0.255	0.063	0.007	-0.079	0.082
Cluster-3	-0.361	-0.460	1	-0.476	-0.063	0.037	0.121	0.064
Cluster-4	-0.200	-0.255	-0.476	1	-0.029	-0.056	-0.074	-0.110
Advanced financial management algorithms along with an experienced human advisor	0.053	0.063	-0.063	-0.029	1	0.547	0.507	0.466
Experienced human advisor who makes use of advanced financial management algorithms	0.003	0.007	0.037	-0.056	0.547	1	0.487	0.402
Advanced financial management algorithms customized with experienced human advisor insights	0.004	-0.079	0.121	-0.074	0.507	0.487	1	0.650
Advanced financial management algorithms customized for your situation	-0.057	0.082	0.064	-0.110	0.466	0.402	0.650	1

21. Correlation Matrix of Clusters and Management Options

Delving deeper, the first relationship examined to test a mediation effect was the clusters and advanced algorithms with an experienced human advisor.

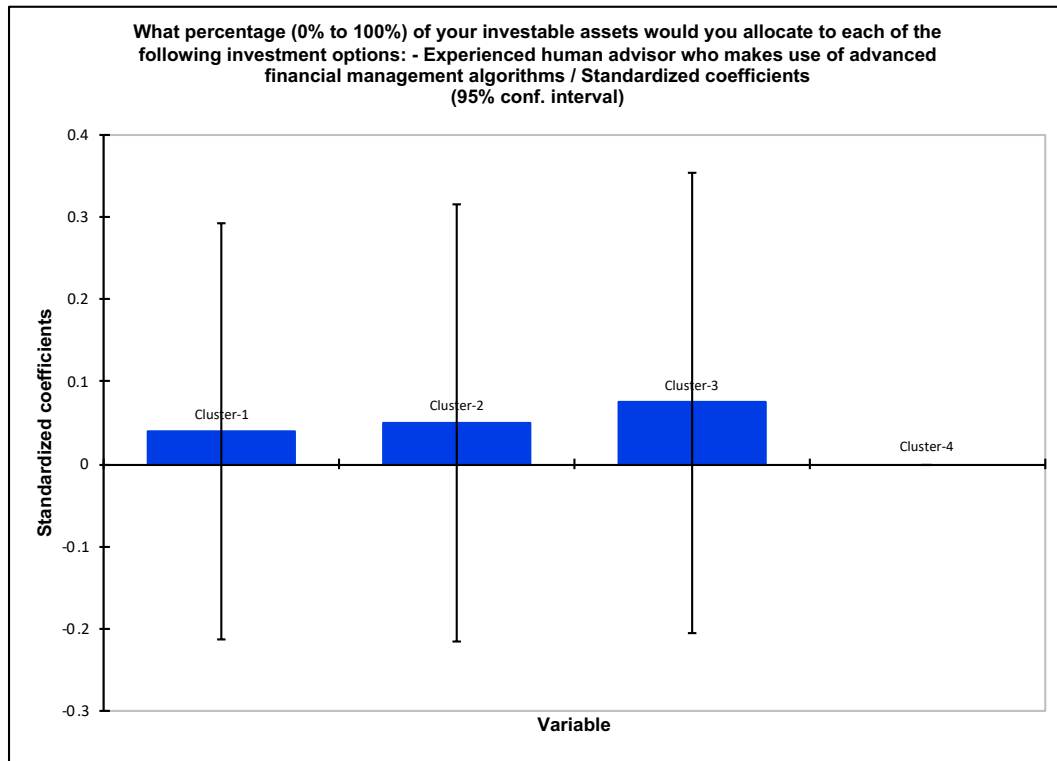


Source	Value	Standard error	t	Pr > t	Lower bound (95%)	Upper bound (95%)
Intercept	48.158	5.406	8.908	< 0.0001	37.412	58.904
Cluster-1	4.463	8.689	0.514	0.609	-12.808	21.734
Cluster-2	4.226	7.751	0.545	0.587	-11.181	19.632
Cluster-3	-0.284	6.515	-0.044	0.965	-13.234	12.666
Cluster-4	0.000	0.000				

22. Option 1 – Cluster Regression Standardized Coefficients

Clusters 1 and 2 had a predictive effect, with coefficients indicating weak positive directionality (Cluster 1 at around .7 and Cluster 2 at .9).

Next was experienced human advisor who makes use of advanced financial management algorithms.

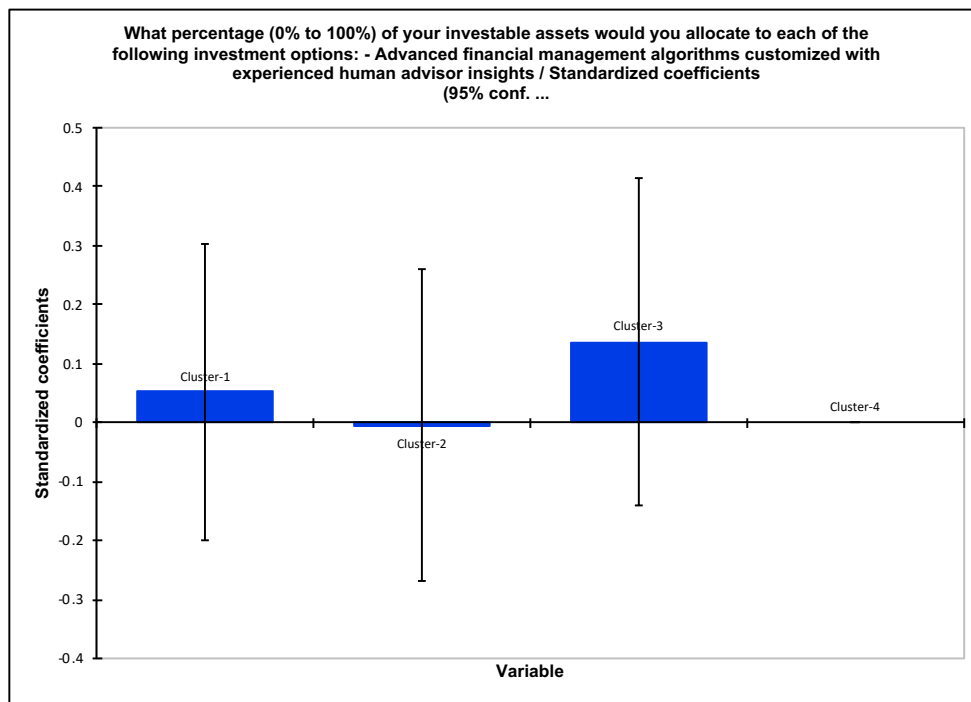


Source	Value	Standard error	t	Pr > t	Lower bound (95%)	Upper bound (95%)
Intercept	47.737	5.011	9.526	< 0.0001	37.776	57.698
Cluster-1	2.526	8.055	0.314	0.755	-13.484	18.535
Cluster-2	2.660	7.185	0.370	0.712	-11.621	16.941
Cluster-3	3.204	6.039	0.531	0.597	-8.800	15.208
Cluster-4	0.000	0.000				

23. Option 2 – Cluster Regression Standardized Coefficients

In this case, all Clusters showed a weak positive directionality; unfortunately, no P-values indicated significance, except for the intercept.

The process iterated for advanced algorithms customized with human advisor insights:

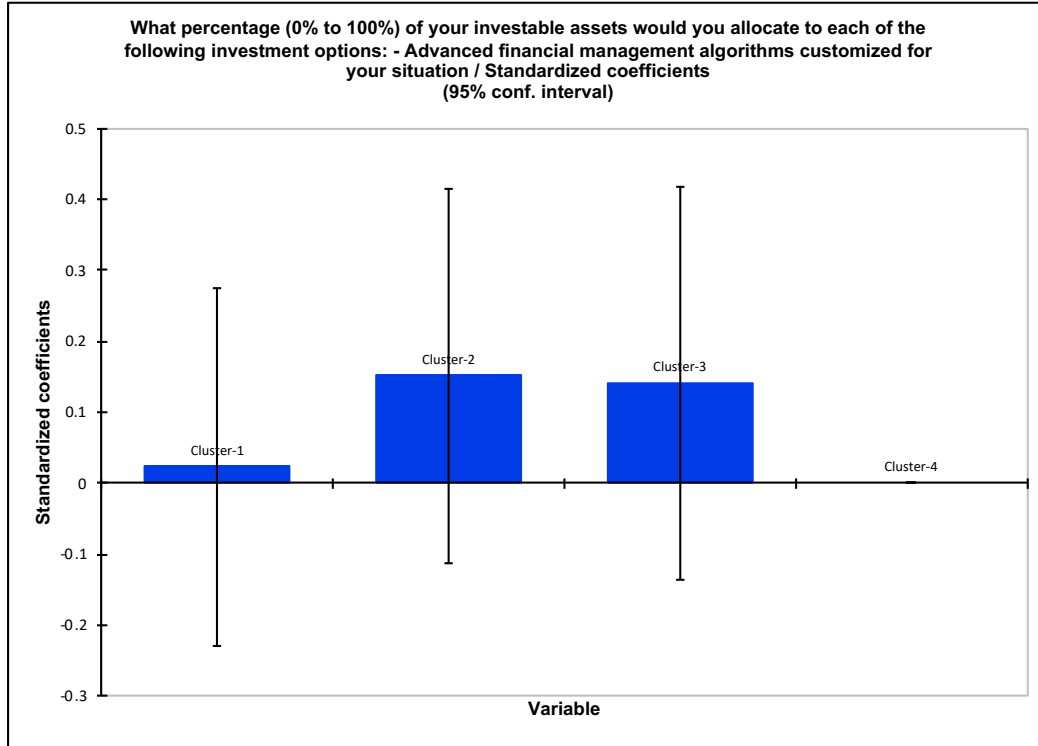


Source	Value	Standard error	t	Pr > t	Lower bound (95%)	Upper bound (95%)
Intercept	40.526	5.758	7.038	< 0.0001	29.081	51.971
Cluster-1	3.815	9.255	0.412	0.681	-14.580	22.211
Cluster-2	-0.349	8.256	-0.042	0.966	-16.758	16.060
Cluster-3	6.797	6.939	0.979	0.330	-6.996	20.590
Cluster-4	0.000	0.000				

24. Option 3 – Cluster Regression Standardized Coefficients

While again dealing with weak significance, the research does show some promise for Cluster 3's positive relationship with a likelihood of using the third option. Interestingly, Cluster 2 demonstrates a negative standardized coefficient for the first time.

Finally, the last option to analyze was Algorithms customized for *your* situation, tapping into the original insight regarding a preference for personal risk levels over even an investment time horizon. To recall, Cluster 2 demonstrated a strong need to weigh personal risk levels.



Source	Value	Standard error	t	Pr > t	Lower bound (95%)	Upper bound (95%)
Intercept	44.928	6.170	7.281	< 0.0001	32.664	57.193
Cluster-1	1.792	9.917	0.181	0.857	-17.920	21.503
Cluster-2	10.087	8.847	1.140	0.257	-7.496	27.670
Cluster-3	7.537	7.436	1.014	0.314	-7.243	22.317
Cluster-4	0.000	0.000				

25. Option 4 – Cluster Regression Standardized Coefficients

This initial finding was confirmed, as Cluster 2 had a strong directionality and close to statistical significance with a need for algorithms customized to their situation. Cluster 3 and 1 also demonstrated positive relationships.

To further test the predictive power of the psychological constructs generated by the principle components analyses, the second factor, engagement, was regressed against the various options to generate a suite of outputs listed below:

26. PCA 2 (Factor of Engagement) Regressions on Likelihood of Use

Option 1: Algorithms with Experienced Human Advisor

Model parameters

Advanced financial management algorithms along with an experienced human advisor):

Category	Source	Value	Standard error	Wald Chi-Square	Pr > Chi²	Wald Lower bound (95%)	Wald Upper bound (95%)
1.000	Intercept	-1.973	1.250	2.490	0.115	-4.423	0.478
	Factor Score 2	-1.232	0.560	4.837	0.028	-2.330	-0.134
2.000	Intercept	0.506	0.501	1.019	0.313	-0.477	1.489
	Factor Score 2	-0.222	0.378	0.345	0.557	-0.963	0.519
4.000	Intercept	1.707	0.434	15.493	< 0.0001	0.857	2.557
	Factor Score 2	-0.131	0.335	0.153	0.696	-0.787	0.525
6.000	Intercept	1.574	0.438	12.925	0.000	0.716	2.432
	Factor Score 2	-0.262	0.335	0.613	0.434	-0.920	0.395

Option 2: Experienced Advisor who uses Algorithms

Model parameters

Experienced human advisor who makes use of advanced financial management algorithms):

Category	Source	Value	Standard error	Wald Chi-Square	Pr > Chi²	Wald Lower bound (95%)	Wald Upper bound (95%)
2.000	Intercept	1.484	1.292	1.319	0.251	-1.048	4.016
	Factor Score 2	1.023	0.586	3.041	0.081	-0.127	2.172
3.000	Intercept	2.388	1.233	3.747	0.053	-0.030	4.805
	Factor Score 2	1.120	0.525	4.548	0.033	0.091	2.150
4.000	Intercept	3.771	1.202	9.841	0.002	1.415	6.127
	Factor Score 2	1.274	0.489	6.780	0.009	0.315	2.233
6.000	Intercept	3.474	1.205	8.308	0.004	1.112	5.837
	Factor Score 2	0.851	0.474	3.222	0.073	-0.078	1.779

Option 3: Algorithms customized with Human Insights

Model parameters (Variable Please indicate the likelihood of using each of the following wealth management options: - Advanced financial management algorithms customized with experienced human advisor insi

Category	Source	Value	Standard error	Wald Chi-Square	Pr > Chi²	Wald Lower bound (95%)	Wald Upper bound (95%)
2.000	Intercept	398.354	39670.821	0.000	0.992	-77355.026	78151.735
	Factor Score 2	122.688	12247.070	0.000	0.992	-23881.127	24126.504
3.000	Intercept	397.844	39670.821	0.000	0.992	-77355.536	78151.225
	Factor Score 2	123.197	12247.070	0.000	0.992	-23880.618	24127.013
4.000	Intercept	399.401	39670.821	0.000	0.992	-77353.979	78152.782
	Factor Score 2	122.806	12247.070	0.000	0.992	-23881.009	24126.622
6.000	Intercept	398.852	39670.821	0.000	0.992	-77354.528	78152.233
	Factor Score 2	122.713	12247.070	0.000	0.992	-23881.103	24126.528

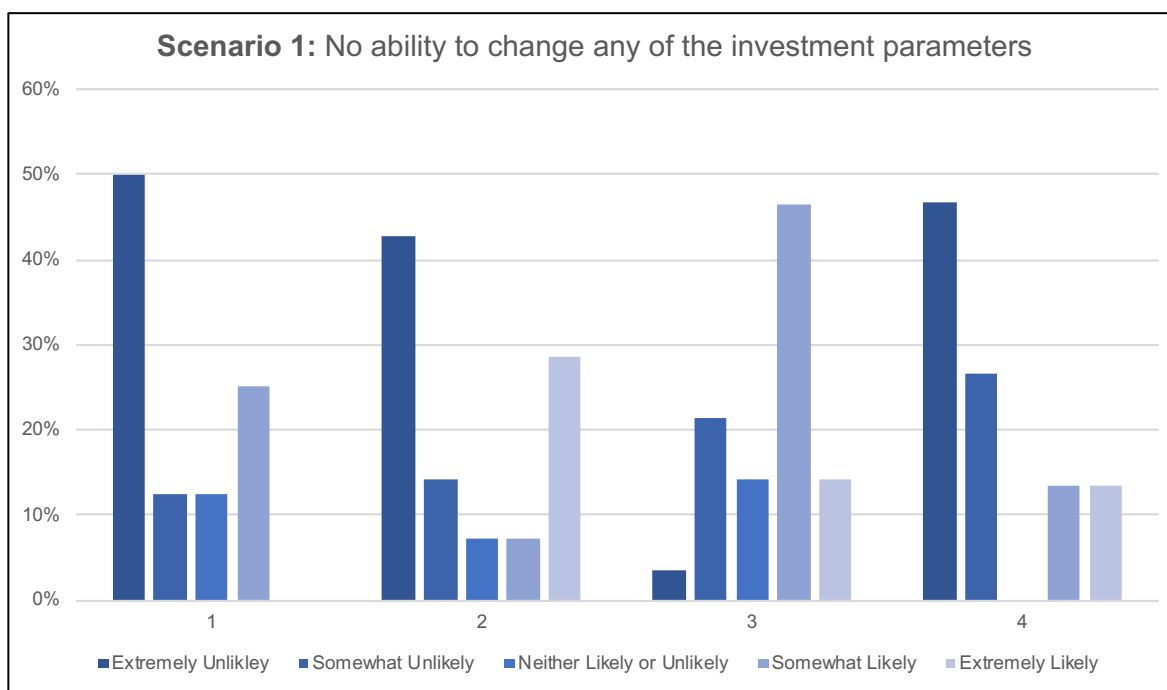
Option 4: Algorithms customized to your situation

Model parameters: Advanced financial management algorithms customized for your situation):

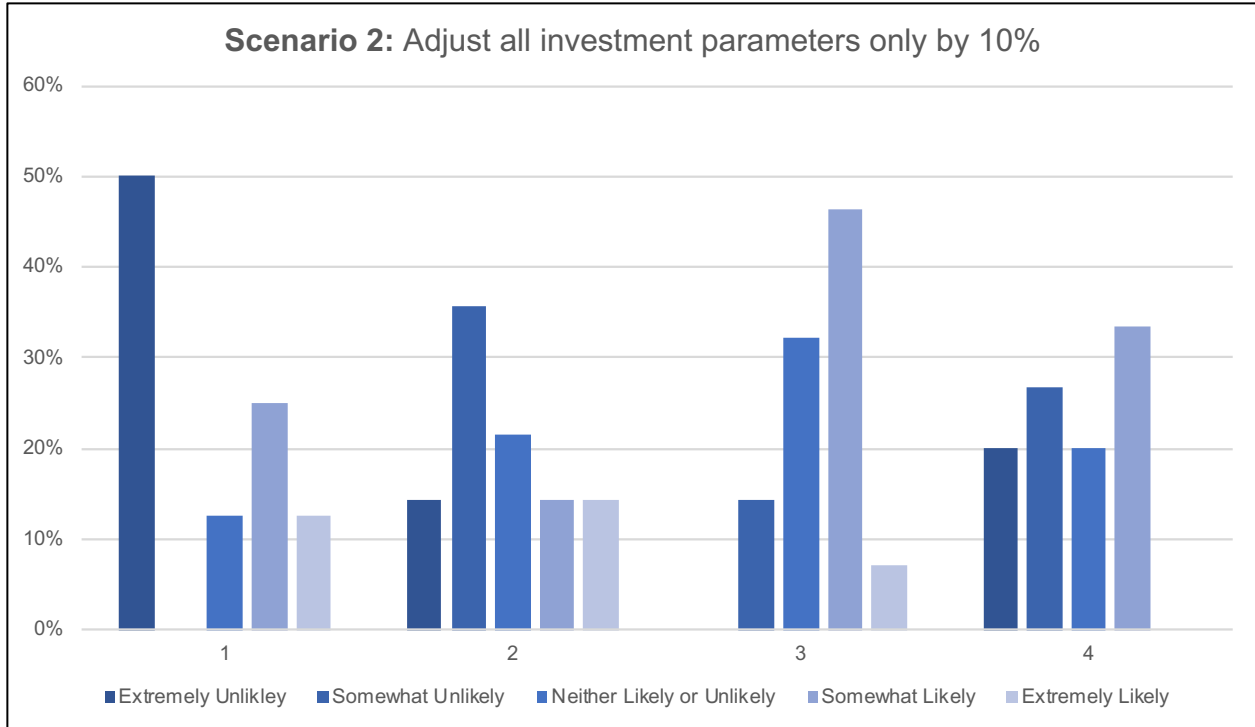
Category	Source	Value	Standard error	Wald Chi-Square	Pr > Chi²	Wald Lower bound (95%)	Wald Upper bound (95%)
2.000	Intercept	1.051	0.602	3.047	0.081	-0.129	2.232
	Factor Score 2	0.555	0.354	2.459	0.117	-0.139	1.248
3.000	Intercept	1.383	0.582	5.635	0.018	0.241	2.524
	Factor Score 2	0.607	0.338	3.222	0.073	-0.056	1.269
4.000	Intercept	1.723	0.565	9.307	0.002	0.616	2.830
	Factor Score 2	0.412	0.310	1.769	0.183	-0.195	1.019
6.000	Intercept	2.084	0.553	14.192	0.000	1.000	3.168
	Factor Score 2	0.383	0.298	1.653	0.199	-0.201	0.968

The main takeaway from this set of data is the fact that little to no statistical significance was generated. The analysis was generated by taking the individual response's factor loading score and regressing this as a dependent variable, holding their multinomial choices from extremely unlikely to extremely likely for each option as the independent variables in the analyses.

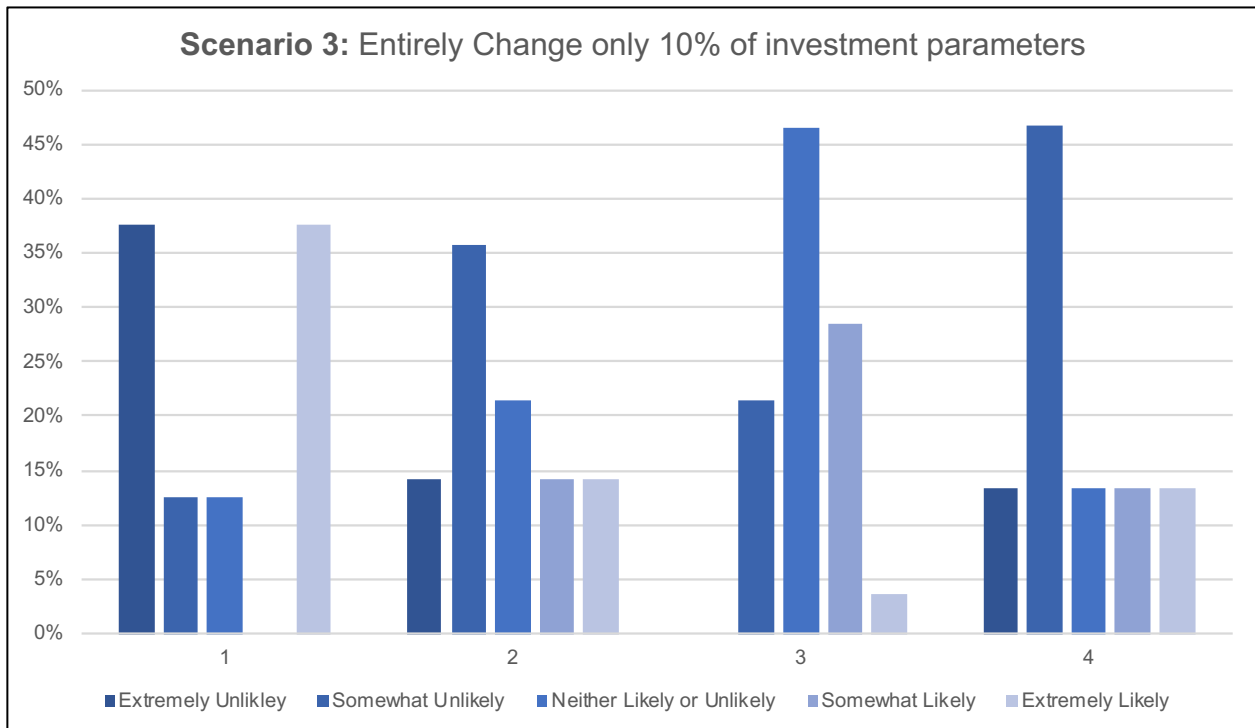
As a corollary to the “Algorithm Aversion” papers discussed in the literature reviews, respondents were posed with three different forms of manipulation over potential investment algorithms. These include (1) no control – where the algorithm decides everything, (2) adjust – where the individual has the ability to affect all parameters, but only by a degree of 10%, and finally (3) change – where the individual can fully change only 10% of the model parameters in the investment algorithm (these would include asset allocation, re-balancing rate, etc...). The preferences of each Cluster in the three different scenarios, as well as the differences are presented below:



17-A: No Change



17-B: Adjust



17-C: Change

Cluster 1 saw a dramatic increase in likelihood when given the option to change some of the parameters. Cluster 2 saw little variation between the change and adjust options and potentially saw the highest probability of engagement in the “no change” option – Cluster 2 definitely seems to be the most susceptible to algorithm aversion, often placing their trust in an advisor who makes use of effective technologies, especially given how versed the cluster is in investing and financial literacy. Cluster 3 sees the largest drop in likelihood when the breadth of parameters they have access to are limited, whereas Cluster 4 definitely values some degree of control, although to what extent they would prefer the adjust option over the change is fairly indiscernible.

CONCLUSION

While a clear mediation was not proven to be significant at a preference level for any of the clusters, interesting insights were discovered for traditional financial advisors, namely regarding Cluster 2. This segment presented immense opportunity as they value attributes that traditional wealth managers pride themselves on and demonstrate a statistically significant relationship in that they are more likely to choose an experienced human advisor over an algorithmic-driven option. Further research investigating Cluster 2 investment behaviors in closer regard, as well as purchase drivers, consumption channels, and willingness to pay, will be beneficial moving forward.